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CHAPTER 12 – MULTIMEDIA: BEHAVIOUR, INTERFACES AND INTERACTION

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12.1 INTRODUCTION

Multimedia here refers to images, audio and video. Multimedia information retrieval means the process of searching for and finding image, audio and video documents through a multimedia search engine. This chapter will take image retrieval as an example to discuss interaction models and interfaces developed for multimedia information retrieval and to illustrate information seeking behaviour in relation to image search.

Current image search engines are mainly based on keyword annotations or information extracted from the image's context (e.g., web page text). This approach has three limitations. First, the manual annotation of images requires significant effort and thus may not be practical for large image collections. Second, as the complexity of the image increases, capturing image content by text alone becomes increasingly more difficult. Finally, it relies on the user being able to articulate and enter a text description of their information need using the same vocabulary (and language) as the text annotations.

In seeking to overcome these limitations, content-based image retrieval (CBIR) was proposed in the early 1990's (Rui et al. 1998), which searches using images rather than keywords as the query (discussed in more detail in chapter 13). CBIR systems have since been primarily used for image searches on collections with limited annotations, or for image searches where annotation is not required, such as trademark search (Eakins et al. 2003). More recently, Google has launched a new application, called "Google Goggles" for Google Android mobile phones, which is a content-based search application and allows people to search for more information about a famous landmark or work of art simply by submitting a photo of that object (Jamaal 2010).

A basic CBIR system interprets the content (e.g. colour, texture and shape, etc.) of the images in a query and in the collection, calculates the similarity between the images in the query and the object images in the collection and ranks the object images in the collection according to their degree of relevance to the images in the query (Marques and Furht 2002).

The content of the images and the entire CBIR search process are not as intuitive nor as user-friendly as they are expected to be. For example, when a CBIR search engine gives high rank to some images in the result because the images are very similar to a query based on the *content* of the images, a user may think the highly ranked images in the search result are not *semantically* relevant at all with respect to the query.

In an effort to bring users into the search loop, relevance feedback techniques are introduced to CBIR. Users now have the opportunity to provide feedback to help refine the query based on previous search result. The system can then learn users' preferences from their feedback to improve the search performance (Lew et al. 2006).

The interaction between the users and the system is vital to be able to learn more useful information from users and better engage the users during the search process. User interaction involves three key elements: a user interaction model, an interactive interface for delivering the user interaction model, and users. These three elements need to combine for effective interaction to happen (Liu et al. 2010).

12.2 USER INTERACTION MODELS

A user interaction model should not only enhance the search performance of a system but also support the interaction between users and the system. A selection of models, which have some similarities, is presented here.

12.2.1 *THREE-DIMENSIONAL SPATIAL MODEL*

Spink et al. (1998) proposed a three-dimensional spatial model, consisting of levels of relevance, regions of relevance and time dimension of relevance, for text retrieval. They firstly applied Saracevic (1996)'s five levels of relevance to indicate why the feedback is relevant, which includes system or algorithmic relevance, topical or subject relevance, cognitive relevance or pertinence, situational relevance or utility, motivational or affective relevance. Second, the regions of relevance indicate the degree of user relevance judgements of feedback. The four regions are: relevant, partially relevant, partially not relevant and not relevant. Third, they proposed a time dimension in their framework, because they found that humans seek information on a particular information problem in stages over time. The time of relevance is measured in formats such as information seeking stage and successive searches. The three-dimensional spatial model is a useful starting point to develop a more advanced user interaction model and better techniques in CBIR.

Other existing research has focused more on single dimensions, such as levels of relevance. Taylor et al. (2007) further showed the importance of the levels of relevance for the information searching process. Their results show that relevance is multi-context and dynamic. Moreover, they also suggested that non-binary relevance assessment is important within every context.

Brini and Boughanem (2003) adapted another dimension – regions of relevance from Spink et al. (1998)'s model to their retrieval system. They demonstrated empirically that partial relevance feedback approach outperformed the binary relevance feedback approach. Wu et al. (2004) and Cheng et al. (2008) applied the regions of relevance to their relevance feedback mechanism for image retrieval. The multi-level relevance measurement was utilized by query expansion and content re-weighting according to relevance level of query images indicated by the user.

12.2.2 *OSTENSIVE MODEL*

Campbell (2000) has focused on the time dimension. He proposed the Ostensive Model (OM) that indicates the degree of relevance relative to when a user found relevant information within the search. The OM includes four ostensive relevance profiles, each of which gives varying importance

to relevant items based on when the item was marked relevant: decreasing, increasing, flat and current profiles, respectively. With the increasing profile the latest relevant items are deemed the most important, whereas with the decreasing profile it is the items marked relevant earliest in the search that are regarded as the most important. With the flat profile all feedback is given equal importance, regardless of when the feedback was provided. Finally, the current profile gives the latest feedback the highest weight while earlier feedback is ignored. Campbell (2000) found that for text-annotated images retrieval the increasing, flat and current profile showed overall better accuracy than the decreasing model, and the increasing profile turned out to be the most robust. Fuhr (2008) suggested that the OM supports the dynamic nature of information needs.

Browne and Smeaton (2004) and Urban et al. (2006) adapted the OM from text retrieval for image and video retrieval to help overcome interaction problems between users and multimedia search system. In their studies, only the increasing profile was applied. The results indicated that whilst users found the OM easy to use, they found it difficult to control the relevance feedback process without greater interaction. Furthermore, the traditional OM accepted only positive feedback, whereas in reality users may wish to refine their searches by providing both negative and positive feedback. Indeed, some research (Pickering and Rüger 2003; Müller et al. 2000) has shown that including negative examples into the relevance feedback can actually help improve the image retrieval accuracy.

12.2.3 PARTIAL AND OSTENSIVE EVIDENCE

Ruthven et al. (2002 and 2003) adapted and combined two dimensions from Spink et al. (1998)'s three-dimensional spatial model, namely: regions of relevance and time, for ranking query expansion terms in text-based information retrieval. The regions of relevance in their study are called partial evidence, which is a range of relevance level from one to ten. In addition, they applied the OM to the time dimension, which is called ostensive evidence. The ostensive evidence is measured by iterations of feedback. Their study shows that combining relevance feedback techniques with the user interaction factors is preferred by users over relevance feedback techniques alone. This model has potential for CBIR.

12.2.4 FOUR-FACTOR USER INTERACTION MODEL

Liu et al. (2009a) proposed an adaptive four-factor user interaction model for CBIR, which combined the three-dimensional spatial model with the OM and, further, added another factor – frequency. The four-factor user interaction model includes: relevance region, relevance level, time and frequency. The four factors will be explained below.

The relevance region factor comprises two parts: relevant (positive) and non-relevant (negative) evidence. Both relevance regions contain a range of relevance level.

The relevance level factor indicates how relevant/non-relevant the evidence is on the related relevance region, which implies a quantitative difference. This factor is measured by a range of relevance level (integers 1-20) indicated by users.

The time factor adapted the four relevance profiles of the OM, which indicates the degree of relevance relative to when the evidence was selected. For example in Figure 1 (a) and (b), the increasing/decreasing profile means ostensive relevance weights for positive/negative examples

increase/decrease respectively with further search iterations. In this model, they applied these ostensive relevance weights to both the positive and negative feedback, and applied the weight to more than one image in every query.

The frequency factor captures the number of appearances of an image in the user selected positive and negative evidence separately across all search iterations.

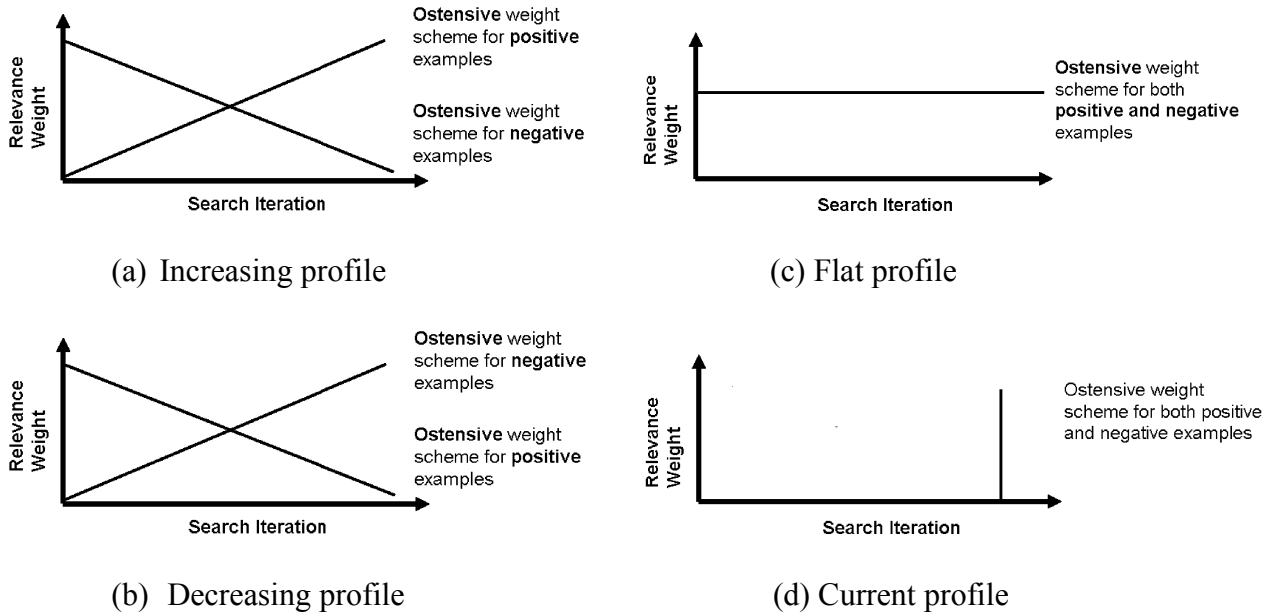


FIGURE 1: FOUR PROFILES OF THE TIME FACTOR

12.3 USER INTERACTIVE INTERFACE

When providing new search mechanism, we need to decide how the mechanism should be delivered to users visually (Bates 1990; White and Ruthven 2006). An interactive user interface delivers the user interaction model visually and supports users in grasping how the model works and how it can be manipulated effectively. These are selections from the literature.

12.3.1 QUERY POINT VS WEIGHT SPACE MOVING

Heesch and Rüger (2003) developed a visual query-by-example search interface based on query point moving (Figure 2 and Figure 3). An image is dragged into a query box, or, e.g. specified via a URL, and the best matching images are displayed in a ranked list to be inspected by the user. Query point moving is a natural extension of such an interface by offering the selection of relevant results as new query elements.

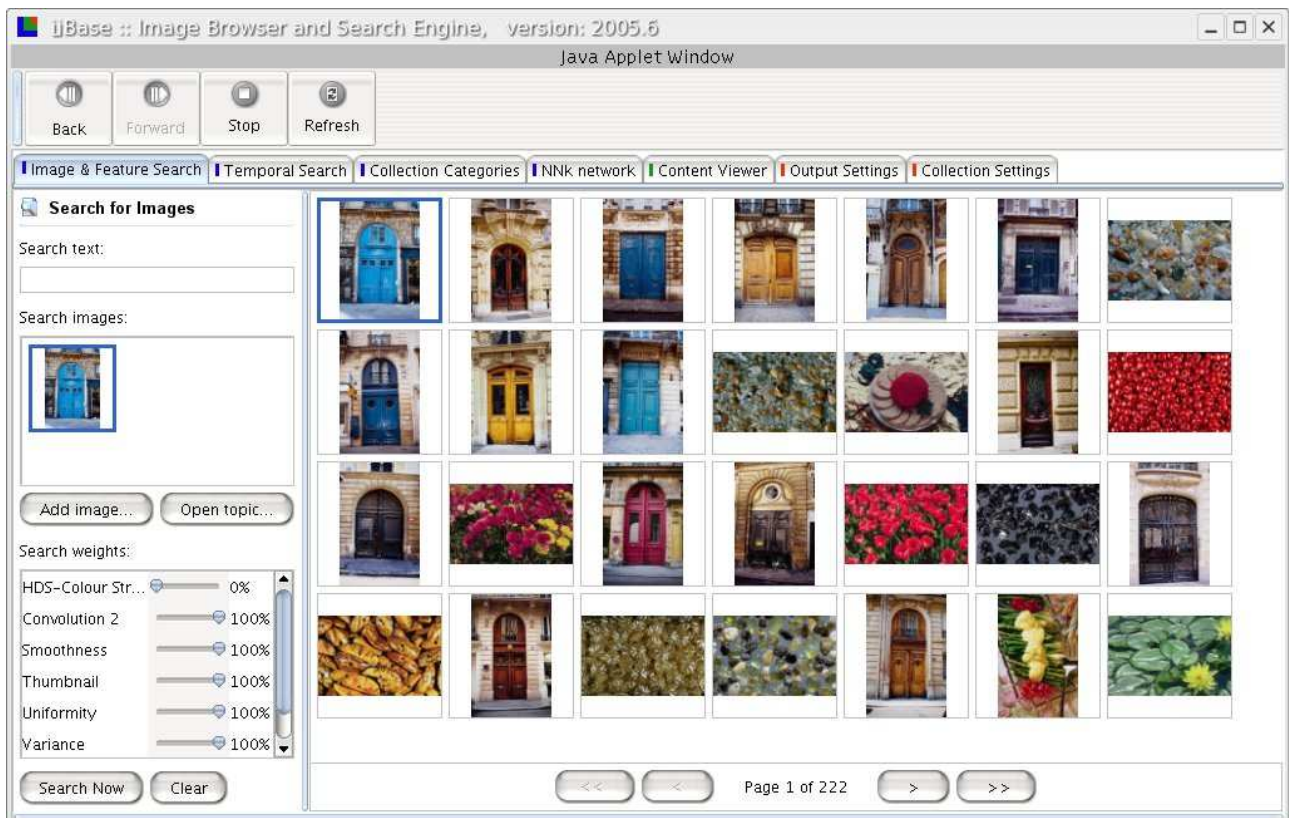


FIGURE 2: QUERY BY EXAMPLE (LEFT PANEL) WITH INITIAL RESULTS IN THE RIGHT PANEL

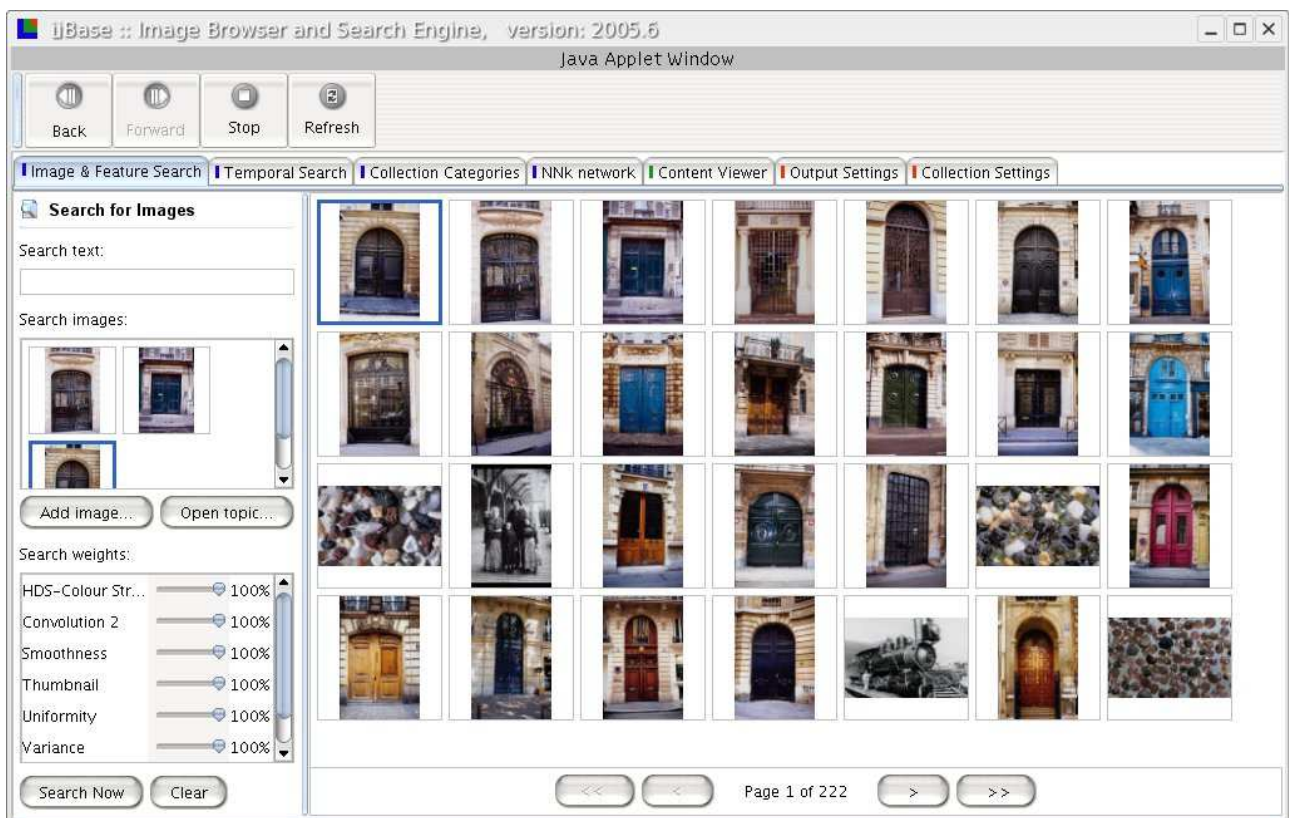


FIGURE 3: A NEW QUERY MADE OF THREE IMAGES FROM FIGURE 2 RESULTS IN MANY MORE DARK-DOOR IMAGES

One other main type of relevance feedback, weight space movement, assumes that the relative weight (meaning importance) of the multitude of content that one can assign to images (e.g. structured metadata fields such as author, creation date and location; content of the image such as

colour, texture and shape; free-form text) can be learned from user feedback (Heesch and Rüger, 2003). The idea is that users can specify the degree to which a returned image is relevant to their information needs. This is done by having a visual representation; the returned images are listed in a spiral, and the distance of an image to the centre of the screen is a measure of the relevance that the search engine assigns to a specific image. Users can now move the image around with the mouse or place them in the centre with a left mouse click and far away with a right click. Figure 4 shows this relevance feedback technique (Rüger, 2010)

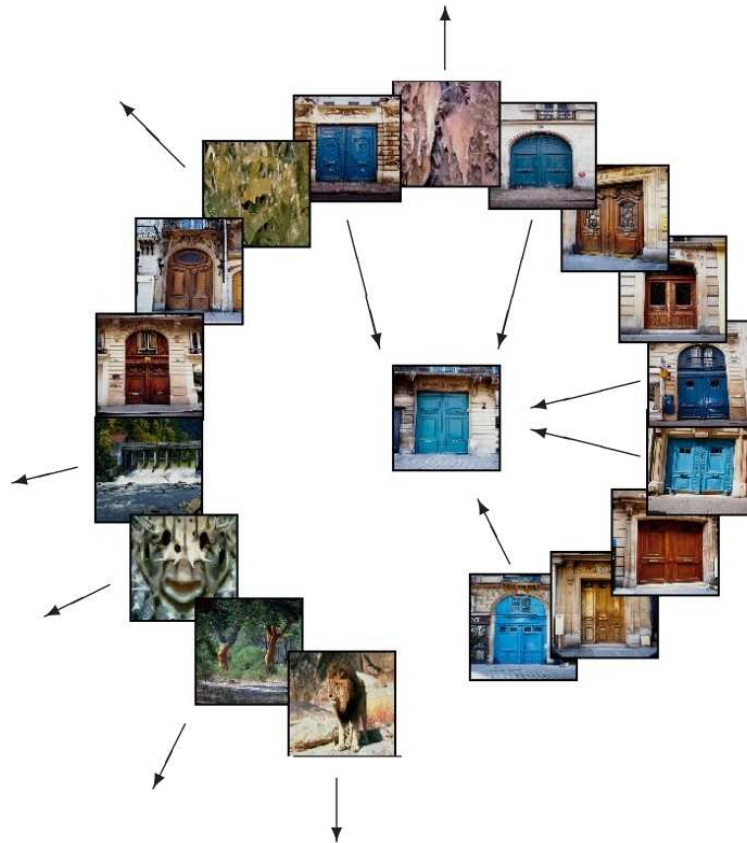


FIGURE 4: A WEIGHT SPACE MOVEMENT RELEVANCE FEEDBACK MODEL

12.3.2 FLEXIBLE IMAGE RETRIEVAL ENGINE (FIRE)

Deselaers et al. (2005) developed a Flexible Image Retrieval Engine (FIRE) that allows users to provide negative feedback from the result set. This is content-based image search engine. Users can provide feedback from the result set to refine the query by selecting any of the three radio buttons – relevant, neutral, and non-relevant – under every result image. The system will try to include the images that are similar to the images indicated as relevant and exclude the images that are similar to the images indicated as non-relevant in the new set of result. The research in (Heesch and Rüger 2003; Pickering and Rüger 2003; Müller et al. 2000) also usefully referred to the importance of providing both negative and positive examples as feedback. Liu et al. (2009a) found that limiting users' selection of negative feedback to the poorest matches in the results will improve search accuracy, but it is not going to be intuitive to users.

12.3.3 OSTENSIVE IMAGE BROWSING

Urban et al. (2006) developed an image search system based on the Ostensive Model. Like FIRE, this is a browsing based search system, which applies a dynamic tree view to display the query path

and results. This interface enables users to re-use their previous queries at a later stage. Whilst the query path is useful, the display becomes overly crowded even after a relatively small number of iterations. This limitation would become even more evident were the system to allow the users to provide negative as well as positive feedback.

12.3.4 EFFECTIVE GROUP ORGANIZATION (EGO)

Urban and Jose (2006) presented Effective Group Organization (EGO), which is a personalised image search and management tool that allows users to search and group the results. The users' groupings are then used to influence the outcome of the results of the next search iteration. This system supports long-term search activity by capturing the users' personalised group history, allowing the users to break and re-commence later without the need to re-create their search groupings from scratch.

12.3.5 IMPLICIT AND EXPLICIT RELEVANCE FEEDBACK

There are two types of interactive feedback for learning users' preferences: explicit feedback and implicit feedback. The explicit feedback is given actively and consciously by the users to instruct the system what to do, whereas implicit feedback is inferred by the system from the way the users have interacted with the system. In other words, explicit feedback means the user is actively controlling the search process whilst implicit feedback means the system is controlling the search process but observes closely use actions.

Heesch and Rüger (2003) evaluated a specific explicit relevance feedback mechanism from image retrieval, while White et al. (2004) deployed a simulation-centric evaluation methodology to measure how well known implicit feedback models learn relevance and improve search effectiveness. Following these, White et al. (2006) later developed an implicit feedback approach for interactive information retrieval. Hopfgartner et al. (2007) model implicit information for interpreting the user's actions with the search engine's interface and suggest that the combination of implicit and explicit relevance feedback provide better search result than explicit relevance feedback alone.

Ruthven et al. (2003) present five user experiments on incorporating behavioural information into the relevance feedback process in information retrieval, concentrating on ranking terms for query expansion and selecting new terms to add to the users' query. Oyekoya and Stentiford (2004) have proposed one particularly interesting device for implicit feedback during the image search process: an eye-tracking device. Their use for visual search was studied by Yang et al. (2002) in terms of psychophysical models. Clough and Sanderson (2004) simulated user interaction with a cross lingual image retrieval system, and in particular the situation in which a user selects one or more relevant images from the top ones; using textual captions associated with the images, relevant images are used to create a feedback model in the Lemur language model for information retrieval, and they show that feedback is beneficial, even when only one relevant document is selected.

12.3.6 UINTERACT

Liu et al. (2009b) propose an interactive content-based image retrieval system – uInteract (Figure 5), based on the four-factor user interaction model (Liu et al. 2009a) described in Section 1.2.4.

This system aims to deliver the four-factor user interaction model visually and allow users to manipulate the model effectively. The key features of the visual interface are:

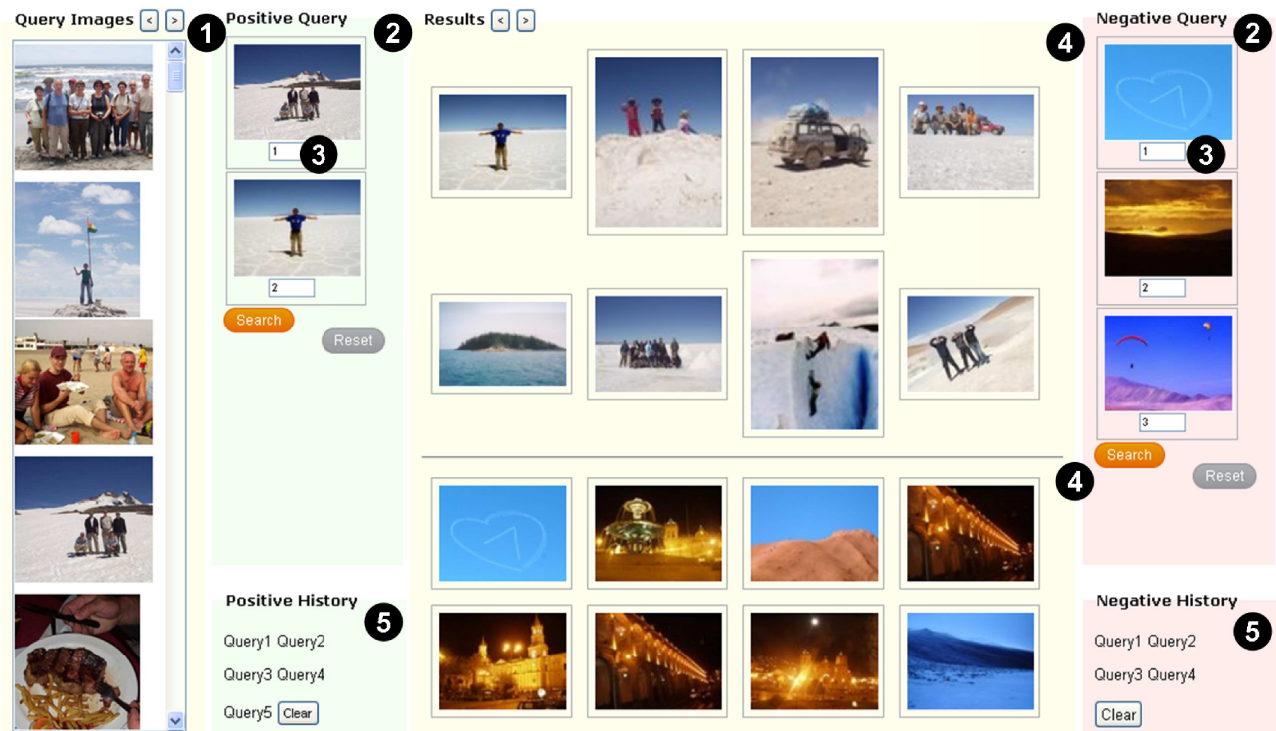


FIGURE 5: THE UINTERACT INTERFACE

- (1) The query image panel is a browsing panel. Users browse the query panel and select one or more images from the provided query images as initial query image(s) to start the search.
- (2) The users can provide both positive and negative examples to a search query, and further expand or reformulate the query. This is a way to deliver the “relevance region” factor of the four-factor user interaction model.
- (3) By allowing the users to override the system automatically generated ranking (integer 1-20) of positive and negative query images, we enable the users to directly influence the importance level of the feedback. The optional “relevance level” factor is generated by the ranking feature.
- (4) The display of the results in the interface takes a search-based linear display format but with the addition of showing not only the best matches but also the worst matches. This feature aims to enable the users to gain a better understanding of the data set where they are searching from.
- (5) The query history not only provides the users with the ability to reuse their previous queries, but it also enables them to expand future search queries by taking previous queries into account. The positive and negative history with the current query together feed the “time” and “frequency” factor of the four-factor user interaction model.

12.3.7 OTHER INTERACTIVE MEDIA RETRIEVAL INTERFACES

Last but not least, Hauptmann et al. (2006) examined extreme video retrieval - an efficient video search mechanism can learn in real-time from user selected relevant feedback and re-rank the result

rapidly based on the combination of text and image similarity and temporal proximity - through two different user interfaces: one with manual result sizing and paging and the other one with automatic sizing and paging. Their findings show that the combined machine and human power performs significantly better than either approach alone, and the manually controlled interface is preferred by users. Further, Hauptmann et al. (2008) improved the extreme video retrieval by expending single keyframe to multiple keyframes per video for both display and analysis. Nguyen and Worring (2008) presented an optimal visualisation scheme on overview, visibility and structure preservation to support user interaction with CBIR search and browsing.

12.4 INFORMATION SEEKING BEHAVIOUR

Information seeking tasks in particular interactive CBIR involves different levels of exploration depending on different user contexts. User contexts can be very different for varying searches by different users. Some people know what they want, and some people only know when they find it (ter Hofstede et al. 1996). Some are patient, but some are not. Some people frequently change their mind on what they are looking for, but some do not. Some people are satisfied with the result they get after a few rounds, but some are not (Urban et al. 2003). These are selected examples based on Information Foraging Theory from the literature.

12.4.1 *EXPLORATORY SEARCH*

Exploratory search is recently emerging to support more user-centric information seeking and interactive search. It aims to shift the research focus from getting the highest search precision toward finding guidance at all stages of the information-seeking process to support a broader set of users' searching and interaction behaviours (White et al. 2007; White and Roth 2009).

Exploratory search is hard to define exactly, as almost all searches are somehow exploratory. However, one definition is that exploratory search is any search with combination of a querying and a browsing strategy to enable learning and investigation (Marchionini 2006; White et al. 2007; Marchionini and White 2009).

White et al. (2007) suggested that exploratory search is related to Information Foraging Theory (Pirolli and Card 1999) in the aspect of finding an optimal path to reach users' information goal during search. For instance, how users search for information based on their information goals, how users apply their searching strategy, and how users decide what information to use, etc. Indeed, Mulholland et al. (2008) have shown that Information Foraging Theory can interpret the effects of the exploratory search technologies.

12.4.2 *INFORMATION FORAGING THEORY*

Information Foraging Theory suggests that the way humans seek information is not unlike the way of wild animals gather food (Pirolli and Card 1999; Pirolli 2007). Information Foraging Theory has three information models: information scent model, information diet model and information patch model. The information scent model explains how the animals find a path to food resource. The information diet model explains what they will select to eat. The information patch model explains how they decide when to hunt elsewhere.

To adapt the food hunting behaviour to human online information seeking, the interpretation will be: foragers will find an information patch that they think would bring the outcome they desire based on their information scents; the foragers then will decide which information resource they will select based on their information diet; the foragers also need to decide how long they will stay with this information patch and when to go to a different patch of information. To decide which information resource is the start point and when to move elsewhere, the foragers need to consider the cost and benefit trade-offs. Different foragers will make different decisions on these stages based on the different contexts.

Liu et al. (2010) proposed and verified a user classification model called ISE model to understand the user interaction with respect to different user types for CBIR based on Information Foraging Theory.

The interpretations of the three information models in CBIR scenario are: the information patch is a set of result images from the initial search; the information scent consists of the clues that users get from task descriptions, query images, result images and past search experience to formulate their information goal and navigate their search process; the information diet is the way that users select the feedback and result images.

The ISE model contains three criteria: information goal (I), search strategy (S) and evaluation threshold (E). There are two different types of user characteristics in each criterion: I – fixed information goal or evolving information goal; S – risky search strategy or cautious search strategy; E – weak evaluation threshold and precise evaluation threshold. Table 1 shows the mapping between the ISE model and Information Foraging Theory and the definition of the six user characteristics of the ISE model based on Information Foraging Theory. A user classification allows us to better understand different type users' search preferences, so that we can develop better systems to support their different search behaviours.

Information Foraging Theory	Criteria of the ISE model	Characteristics of the ISE model	Definition of the characteristics
Information scent model	Information goal	Fixed	Searchers with fixed information goal know what they are looking for
		Evolving	Searchers with evolving information goal are not sure what they are looking for
Information patch model	Search strategy	Cautious	Searchers with cautious search strategy move slowly between patches
		Risky	Searchers with risky search strategy move quickly between patches
Information diet model	Evaluation threshold	Weak	Searchers with weak evaluation threshold are lenient on selecting the results
		Precise	Searchers with precise evaluation threshold are strict on selecting the results

Table 1: Definition of the ISE model based on Information Foraging Theory

12.5 SUMMARY

This chapter emphasised the importance of the user interaction to multimedia information seeking, especially to content-based image retrieval. To enable an effective interaction, we need a good user interaction model, a good user interactive interface and a good understanding of users' information

seeking behaviours. The brief overview of the three key elements of user interaction presents how the interaction mechanisms, interface design and the search behaviours change over time.

Currently, a new and relatively unexplored area for improving user interaction is the social context information. By looking not only at the behaviour and attributes of users, but also their past interactions and also the interactions of people with whom they have some form of social connection could yield useful information when developing user interaction models, designing interaction interfaces and understanding search behaviours.

As text-based retrieval has much longer history than content-based retrieval, many of the user interaction models applied in content-based retrieval are adapted from text-based retrieval. However, the content-based retrieval is fundamentally different from text-based retrieval because they have different search objects, such as texts/keywords/annotations for text-based retrieval, images/videos/music for content-based retrieval. Therefore, the adapted interaction models need to be carefully tailored for specific content-based search. Further, the interface design of the content-based search systems will be different from text-based search systems because the different search objects and interaction mechanisms, although they all follow the same general interface design guidelines. Finally, there are lots of similarities between text-based and content-based user search behaviour, therefore, the user classification models developed based on user search behaviour and preferences could be shared between the two types of search systems.

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